Have Financial Markets Become More Informative?

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Abstract

The finance industry has grown. Financial markets have become more liquid. Information technology has been revolutionized. Have market prices become more informative? We use stock and bond prices to forecast earnings and find that the information content of market prices has not increased since 1960. We use a model with information acquisition and investment to link financial development, price informativeness, and investment. As information costs fall, the predictable component of future earnings rises, improving capital allocation and enhancing welfare. We find that this component has remained stable in the data. Our model also allows us to decompose price informativeness into two components, one produced in markets, the other reflected by them. Both are unchanged. Prices have become stronger predictors of R&D investment, but this has not translated into stronger earnings predictability.

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1 Introduction

Fama (1970) writes, “The primary role of the capital market is allocation of ownership of the economy’s capital stock. In general terms, the ideal is a market in which prices provide accurate signals for resource allocation: that is, a market in which firms can make production-investment decisions... under the assumption that security prices at any time ‘fully reflect’ all available information.” In an ideal market, therefore, prices convey strong information about productivity, and this information drives investment. To assess progress towards this ideal, we measure the information content of prices by using them to predict earnings and investment. We trace the evolution of price informativeness in the U.S. over the last five decades.

During this period, a revolution in computing has transformed finance: Lower trading costs have led to a flood of liquidity.\footnote{In 1960, the typical share turned over once every five years; today it does so every three to four months.} Modern information technology delivers a vast array of data instantly and at negligible cost. Concurrent with these trends, the finance industry has grown, its share of GDP more than doubling. Within this context, we ask: Have market prices become more informative?

Our first task is to come up with the right measure of informativeness. We build a model that combines Tobin’s (1969) $q$-theory of investment with the noisy rational expectations framework of Grossman and Stiglitz (1980). When more information is produced, prices become stronger predictors of earnings. We call the standard deviation of the predictable component of earnings price informativeness and we show that it is directly related to welfare, as in Hayek (1945): information promotes the efficient allocation of investment, which leads to more growth.

Our main results are based on regressions of future earnings on current valuation ratios, controlling for current earnings. We look at both equity and bond markets. We include one-digit industry-year fixed effects to absorb time-varying cross-sectional differences in the cost of capital. This regression asks whether two firms in the same sector with different
market valuations tend to have different earnings. The answer is yes, but the amount of informativeness is unchanged since 1960.

By itself, constant price informativeness does not imply constant information production in markets. It is possible that information production has simply migrated from inside firms to markets. Bond, Edmans, and Goldstein (2012) distinguish between the revelatory component of price informativeness, which they call real price efficiency (RPE), and the forecasting component, forecasting price efficiency (FPE). The financial sector adds value only to the extent that it reveals information that would otherwise be unavailable to decision makers.

Of course, almost any bit of information is revelatory to someone, so total price informativeness remains of interest. Nevertheless, we take note from Bond, Edmans, and Goldstein (2012) and seek to disentangle RPE from FPE. Our model provides a way of doing so. When managers rely on prices, they import the price noise into their investment policies. When markets reveal no new information, managers ignore them and prices remain noisy but investment does not. In the opposite case, when all information is produced in markets, managers use prices and both investment and prices are equally noisy. In other words, more information increases the predictive power of both prices and investment, but a rise in the revelatory component of prices increases price informativeness disproportionately.

To see if the constant price informativeness could mask a substitution from forecasting (FPE) to revealing (RPE) information, we check to see if the predictable component of earnings based on investment has changed. We find it has not. Based on our model, this implies that neither RPE nor FPE has risen.

To rule out the possibility that an increase in noise, or discount rate variation, also masks greater information production, we run regressions of ex post returns on prices. Our results show that discount rate variation has also remained stable.

Our strongest positive finding is that a higher equity valuation is more closely associated with R&D investment now than in the past. The same is not true of capital expenditure.
However, the increased predictability of R&D is not related to increased predictability of earnings, so we cannot conclude that informativeness has increased.

For most of the paper, we examine S&P 500 stocks whose characteristics have remained stable. In contrast, running the same set of regressions on the universe of stocks appears to show a decline in informativeness. We argue, however, that this decline is consistent with changing firm characteristics: the typical firm today is more difficult to value. This motivates our focus on S&P 500 firms.

We note that a rise in uncertainty cannot explain our results but instead deepens them. In our model, greater uncertainty increases informativeness as it provides greater opportunity to investors who compete with each other. In the data, we see an increase in the dispersion of ex post earnings among all stocks, which is consistent with greater uncertainty. This is not the case among S&P 500 firms, on which most of our analysis is based.

It remains possible that S&P 500 firms have also changed even if their observable characteristics appear stable. For example, disclosure rules have changed over time. To control for this possibility, we run a cross-sectional test. Specifically, we compare the price informativeness of firms that have CBOE-listed options, to that of firms that do not. Option markets provide greater opportunity for traders to express negative views, take higher leverage, and tailor their positions. These factors should spur information production. Instead, we find that price informativeness is the same for CBOE-listed and unlisted stocks.

We conclude our analysis with a model-free measure of informativeness based on earnings surprises (in terms of returns) since 1990. For S&P 500 firms, we find that earnings surprises have doubled, even as total volatility is flat. For all firms, both earnings surprises and total volatility have risen. Earnings announcements are accompanied by a surge in trading volume, a recent phenomenon. Results hold even within firms.

The rest of this paper proceeds with an overview of the related literature, followed by our model, empirical results, and concluding remarks.
2 Literature Review

Over the last 30 years, the U.S. financial sector has grown six times faster than GDP (Financial Times).\(^2\) At its peak in 2006, the financial sector contributed 8.3% to U.S. GDP compared to 4.9% in 1980 and 2.8% in 1950 (see Philippon (2008) and Greenwood and Scharfstein (2012) for more detailed measures). A classic literature studies the impact of the financial sector on economic growth (Levine (2005) provides a survey).\(^3\) Greenwood and Jovanovic (1990), among others, argue that finance accelerates innovation and growth by producing information that improves the allocation of resources.

More recently, the financial crisis of 2007–2009 led to a challenge of the idea that finance promotes growth. Rajan (2005) suggests that financial complexity raises the probability of a catastrophic meltdown. Gennaioli, Shleifer, and Vishny (2011) show that in the presence of neglected tail risks, financial innovation can increase fragility. Bolton, Santos, and Scheinkman (2011) provide a model in which rents in the financial sector attract an excessive share of human capital. By relating financial sector output to its cost, Philippon (2012) finds that the unit cost of financial intermediation has increased in recent decades.

It is difficult to discern a clear relationship between financial sector growth and aggregate growth in U.S. data. It is likely that aggregate growth is driven by many factors other than finance. A more powerful test exploits cross-sectional variation. In this line, Rajan and Zingales (1998) and Morck, Yeung, and Yu (2000) use cross-country variation in financial development. Our approach is to consider firm-level variation, which allows us to study the evolution of markets in the U.S. over time.

We contribute to the finance-and-growth literature by examining the information channel empirically. We measure the extent to which market valuations differentiate firms that

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\(^2\)“Why dealing with the huge debt overhang is so hard” by Martin Wolf, Financial Times, January 27, 2009.

\(^3\)In his survey of the literature on financial development and growth, Levine (2005) splits the role of the financial industry into five broad functions: 1) information production about investment opportunities and allocation of capital; 2) mobilization and pooling of household savings; 3) monitoring of investments and performance; 4) financing of trade and consumption; 5) provision of liquidity, facilitation of secondary market trading, diversification, and risk management. Our focus is on (1).
will have high ex-post profits from those that will not. We call the resulting predictable component of profitability price informativeness and we track it over five decades. Higher price informativeness facilitates the efficient allocation of resources by lowering the cost of capital for profitable firms and by directing investment inside those firms. In this way, price informativeness has a direct impact on welfare.

A large literature with seminal papers by Grossman and Stiglitz (1980), Glosten and Milgrom (1985), Kyle (1985), and Holmström and Tirole (1993) studies the incentives of traders to produce new information. A general result is that prices must be somewhat confounding, or “noisy”, to compensate traders for the cost of mining new information. As financial technology develops and this cost shrinks, the information content of prices increases. Our goal is to use this proposition to back out changes in the efficiency of information production from the level of informativeness in prices.

Bond, Edmans, and Goldstein (2012) survey the literature on information production, emphasizing the challenge of separating the genuinely new information produced in markets, which they call real price efficiency, from the information that is already known and merely reflected in prices, or forecasting price efficiency. We follow their lead and seek to disentangle the two. Our model provides conditions under which this is possible. We also note that few pieces of information, if any, are known to every decision maker they affect. While firm managers arguably possess a highly refined information set, others may not. For example, potential industry entrants, competitors, customers, creditors, or regulators may benefit from the role of prices in summarizing a firm’s financial statements. For this reason, we are also interested in total informativeness, different parts of which are revelatory to different agents.

A number of papers provide empirical evidence for the link between prices and investment. Chen, Goldstein, and Jiang (2007) show that the price sensitivity of corporate investment is stronger when prices contain more information (based on microstructure measures) that is not otherwise available to firm managers. Sunder (2004) and Baker, Stein, and Wurgler (2003) show that a stock price increase eases the financing constraints of firms and enables
them to increase investments. Bond, Edmans, and Goldstein (2012) provide additional references.


Our main contribution is to strengthen the empirical counterpart to this extensive theoretical literature by constructing theoretically-grounded, welfare-based measures of price informativeness and its revelatory and forecasting components. We trace the evolution of these measures over a period characterized by unprecedented growth in information technology and market liquidity. In this way, our paper provides a broader empirical analysis of the information channel in the U.S. than has been previously undertaken.

Price informativeness is also affected by disclosure, and changes in disclosure have received strong attention in the accounting literature (see the surveys by Healy and Palepu (2001) and Beyer, Cohen, Lys, and Walther (2010)). Although major regulatory actions such as Reg. FD in 2000 and Sarbanes-Oxley in 2002 have been implemented, the question of their effects on disclosure is unsettled.4 There is also conflicting evidence on whether Reg. FD led to a decrease in information asymmetry among investors.5 It is even less clear how such

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4Heflin, Subramanyam, and Zhang (2003) find no evidence of increased volatility around earnings announcements after Reg. FD, or significant deterioration in analyst forecast accuracy, which suggests that the information available to market participants was not reduced. In contrast, Wang (2007) reports that after the passage of Reg. FD, some firms cut back on issuing earnings guidance. However, Bushee, Matsumoto, and Miller (2004) provide evidence that disclosure remained constant or even increased after the passage of Reg. FD. Kothari, Ramanna, and Skinner (2009) find that firms reduced their withholding of bad news relative to good news after Reg. FD was implemented.

5Bushee, Matsumoto, and Miller (2004), Gintschel and Markov (2004), and Eleswarapu, Thompson, and Venkataraman (2004), find a decrease in bid-ask spreads after Reg. FD. Others find the opposite: Sidhu, Smith, Whaley, and Willis (2008) suggest that the adverse selection component of the bid-ask spread increased after Reg. FD.
disclosure regulation has affected price informativeness. Our main tests do not provide a way to control for changes in disclosure, though we examine the periods surrounding well-known regulatory initiatives such as Reg FD in 2000 and Sarbanes-Oxley in 2002. We also provide cross-sectional results using option listings that hold disclosure rules fixed.

A second related strand of the accounting literature studies value relevance, the impact of accounting metrics on market values (Holthausen and Watts 2001). Our approach is to measure the extent to which market values predict—as opposed to react to—accounting metrics, specifically earnings and investment.

While our focus is on long-term trends in price informativeness, other studies consider business-cycle variation in information production. For example, in Van Nieuwerburgh and Veldkamp (2006), information production rises in booms. This dynamic is absent from our model, but our time series informativeness measure do fluctuate at business cycle frequencies (for example, informativeness drops sharply after the end of the NASDAQ boom in 2000).

In sum, our paper lies at the intersection of the finance-and-growth and information-production literatures. Our contention is that measuring the information content of prices helps to assess the social value of a growing financial sector.

3 Model

We link financial development, information production, investment, and welfare by combining the noisy rational expectations framework of Grossman and Stiglitz (1980) with Tobin’s (1969) q-theory of investment. Traders produce information that is aggregated in markets and used by managers in setting investment. In turn, managers produce internal information that is revealed to market participants through investment. We highlight the role of prices in promoting efficient investment, or real price efficiency (RPE), and show how to distinguish RPE from forecasting price efficiency (FPE). Our model generates comparative statics on the relationships between financial development, fundamental uncertainty, and price infor-
mativeness. We develop welfare-based measures of informativeness that we take to the data in the next section.

Consider an economy that evolves over three dates, \( t = 0, 1 \) and 2. On date 0, traders purchase the strength of their signals. Trading and investment take place simultaneously on date 1. Final payoffs are realized on date 2. We develop and solve the model from date 2 backwards.

A. Investment

On date 2, a firm delivers profits of

\[
v(k) = zk - k - \frac{\gamma}{2}k^2,
\]

where \( z \sim N(1, \sigma_z^2) \) is productivity and \( k \) is investment subject to a quadratic adjustment cost. Uncertainty about productivity together with costly investment create demand for information. We allow for information to originate both in markets and inside the firm as well as to flow from one side to the other.

Let \( \theta = (z - 1) + \epsilon^\theta \), a linear signal with precision \( h_\theta/\sigma_z \) and total variance \( \sigma_\theta^2 \), be a sufficient statistic for the information contained in prices with \( \epsilon^\theta \perp z \). We will derive \( \theta \) endogenously from prices. Also let \( \eta = (z - 1) + \epsilon^\eta \), a linear signal with precision \( h_\eta/\sigma_z \) and total variance \( \sigma_\eta^2 \), be a private signal available to the firm’s manager with \( \epsilon^\eta \perp z \) and \( \epsilon^\eta \perp \epsilon^\theta \).

For example, the manager may have access to soft information about the firm’s investment opportunities. The manager forms a conditional estimate

\[
E[z | \theta, \eta] - 1 = \left( \frac{1}{h_\theta^2 + h_\eta^2} \right) \left( h_\theta^2 \theta + h_\eta^2 \eta \right).
\]

The manager’s reliance on prices is increasing in their precision \( h_\theta \) and decreasing in the

\[\text{\footnotesize{Thus } } \sigma_\theta^2 = \sigma_z^2 \left( 1 + 1/h_\theta^2 \right) \text{ and } \sigma_\eta^2 = \sigma_z^2 \left( 1 + 1/h_\eta^2 \right).\]
precision of internal information \( h_\eta \). The optimal investment policy maximizes firm value:

\[
k^* (\theta, \eta) = \operatorname{argmax}_k E[v(k)|\theta, \eta] = \frac{1}{\gamma} (E[z|\theta, \eta] - 1). \tag{3}
\]

This is the classic \( q \)-theory investment equation. A strong signal leads to high investment, and from (2), the investment response is increasing in precision. Information facilitates efficient investment. In fact, since the unconditional mean of productivity is one, information is necessary for investment. Though this particular specification can be modified, it highlights the link between information and growth. We link information and welfare through wealth in the following proposition:

**Proposition 1.** Ex-ante wealth is increasing in total informativeness, which is given by

\[
\sqrt{\text{Var}(E[z|k^*])} = \frac{\sigma_z}{\sqrt{1 + \frac{1}{h_\theta^2 + h_\eta^2}}}. \tag{4}
\]

**Proof.** Write the maximized firm value

\[
E[v(k^*)|\theta, \eta] = \frac{1}{2\gamma} (E[z|\theta, \eta] - 1)^2. \tag{5}
\]

Aggregating across realizations, the ex-ante firm value is

\[
E[v(k^*)] = \frac{1}{2\gamma} \text{Var}(E[z|\theta, \eta]). \tag{6}
\]

Thus, ex-ante wealth is increasing in \( \text{Var}(E[z|\theta, \eta]) \). Since \( k^* \) is linear in \( E[z|\theta, \eta] \) by (3), \( \text{Var}(E[z|\theta, \eta]) = \text{Var}(E[z|k^*]) \). Taking variances on both sides of (2) verifies the formula as stated. \( \Box \)

Information increases the value of the firm’s real option via the manager’s ability to respond by optimizing investment. Welfare, as proxied here by wealth, is increasing in managers’ screening ability, measured here by the dispersion of conditional expected productivity.
across firms. This dispersion is also reflected in the distribution of investment across firms. We note that total informativeness can be calculated as the predicted variation (the coefficient times the standard deviation of the regressor) from a regression of productivity $z$ on investment $k$.

Since our focus is on markets, we are interested in the market component, which comes from $\theta$. A key challenge lies in extracting $\theta$ from prices since prices also depend on $\eta$. In other words, we seek to separate RPE (managers learning from prices, $\theta$) from FPE (investors learning from managers, $\eta$). In the next section, we show that this can be achieved by running separate regressions of productivity on investment and prices.

B. Trading

The market signal $\theta$ is produced by investors and transmitted via prices. On date 1, a measure-one continuum of informed traders receive a common signal $s = (z - 1) + \epsilon^s$ with precision $h_s/\sigma_z$, total variance $\sigma_s^2$, and $\epsilon^s \perp \epsilon^\eta$. In practice, the traders’ signal could also be correlated with the internal signal, but only the orthogonal component represents a contribution to RPE.

Traders also observe prices, which are summarized by $\theta$, and investment $k^*$, which reveals $\eta$ given $\theta$ by (3). Assuming that investment is public preserves the linearity of the traders’ filtering problem, which makes the model tractable. In the absence of agency frictions, managers have an incentive to communicate their investment plans. If they cannot or choose not to do so, the model may overstate the link between prices and investment. Our analysis does not provide a way to control for changes in disclosure, though we examine the periods surrounding well-known regulatory actions such as Reg FD in 2000. We also provide cross-sectional results that hold disclosure rules fixed.

Informed traders maximize expected wealth subject to a quadratic position cost $\alpha$. The position cost leads to an interior solution for $x$. It can be interpreted as reduced-form risk.

\footnote{Thus, $\sigma_s^2 = \sigma_z^2 (1 + 1/h_s^2)$.}
aversion or a cost of under-diversification more broadly, and it enters analogously to the adjustment cost $\gamma$ in the manager’s problem. Normalizing the interest rate to zero, traders solve

$$\max_x E [x (v (k^*) - p)] | s, \eta] - \frac{\alpha}{2} x^2. \quad (7)$$

The assumption that $s$ is common among traders allows us to drop $\theta$ from the conditioning set. The optimal portfolio demand is

$$x^* = \frac{1}{\alpha} (E [v (k^*)] | s, \eta] - p) \quad (8)$$

$$= \frac{1}{\alpha} \left[ E [z | s, \eta] k^* - k^* - \frac{\gamma}{2} (k^*)^2 - p \right]. \quad (9)$$

To allow for noise in prices and to provide an incentive to acquire information, we follow Grossman and Stiglitz (1980) and introduce a set of noise traders who demand $ku$ shares with $u \sim N (0, \sigma_u^2)$. We think of noise traders as being endowed with an inaccurate signal yet acting on it, which leads to demand proportional to $k^*$ as with informed traders. The firm issues one share. The market clearing condition is $x + k^* u = 1$ and so

$$p = E [v (k^*)] | s, \eta] - \alpha (1 - k^* u) \quad (10)$$

$$= \left[ E [z | s, \eta] k^* - k^* - \frac{\gamma}{2} (k^*)^2 \right] - \alpha (1 - k^* u). \quad (11)$$

High prices reflect either high fundamentals $E [z | s, \eta]$ or a low “discount rate” $-u$. Substituting for $E [z | s, \eta]$, prices are given by

$$p = \left( \frac{1}{h_s^2 + h^2 s} \frac{1}{h^2 s + h^2 \eta} \right) (h_s^2 s + h^2 \eta) k^* - \frac{\gamma}{2} (k^*)^2 - \alpha (1 - k^* u). \quad (12)$$

From the manager’s standpoint, a sufficient statistic for the additional information contained
in prices is

$$\theta = s + \frac{1}{h_s^2} \left( \frac{1 + \frac{1}{h_s^2 + h_q^2}}{h_s^2 + h_q^2} \right) \alpha u. \quad (13)$$

The manager orthogonalizes prices with respect to internal information to extract the revelatory component $\theta$, which contributes to RPE. Relying on $\theta$ does not come without cost, however, since it introduces noise into investment. The precision of $\theta$ is given by

$$\frac{1}{h_\theta^2} = \frac{1}{h_s^2} + \left[ \frac{1}{h_s^2} \left( \frac{1 + \frac{1}{h_s^2 + h_q^2}}{h_s^2 + h_q^2} \right) \right]^2 \alpha^2 \sigma_u^2 \sigma_z^2. \quad (14)$$

RPE falls to zero when traders collect no information ($h_s^2 \to 0$), and it approaches an upper bound given by the noise in prices when traders have infinite precision ($h_s^2 \to \infty$). Interestingly, RPE is decreasing in the quality of internal information. When internal information is very precise, it dominates prices and crowds out the traders’ signal. This raises the possibility that a substitution from internal to market-based information, perhaps driven by increased market liquidity, could leave informativeness unchanged even as it increases RPE. To check this possibility, we need a way to separate the traders’ signal from the internal signal. The following result helps us do so.

**Proposition 2.** Price informativeness is given by

$$\sqrt{\text{Var} \left( E \left[ z | p/k^* \right] \right)} = \frac{\sigma_z}{\sqrt{\left(1 + \frac{1}{h_s^2 + h_q^2}\right) + \left(1 + \frac{1}{h_s^2 + h_q^2}\right)^2 \alpha^2 \sigma_u^2 \sigma_z^2}}. \quad (15)$$

Moreover,

$$\lim_{h_s^2 \to \infty, h_q^2 \to 0} \frac{\sqrt{\text{Var} \left( E \left[ z | p/k^* \right] \right)}}{\sqrt{\text{Var} \left( E \left[ z | k^* \right] \right)}} = 1 \quad (16)$$

$$\lim_{h_s^2 \to 0, h_q^2 \to \infty} \frac{\sqrt{\text{Var} \left( E \left[ z | p/k^* \right] \right)}}{\sqrt{\text{Var} \left( E \left[ z | k^* \right] \right)}} = \frac{1}{\sqrt{1 + \alpha^2 \sigma_u^2 \sigma_z^2}}. \quad (17)$$
Proof. From (12), taking out constants and conditioning on investment \( k^* \), the full information contained in prices can be extracted from the price-to-assets ratio

\[
p/k^* \propto \left( \frac{\frac{1}{h^2_s + h^2_{q}}}{1 + \frac{1}{h^2_s + h^2_{q}}} \right) \left( h^2_s s + h^2_q \eta \right) + \alpha u. \tag{18}
\]

Price informativeness, the predicted variation from a regression of \( z \) on \( p/k^* \) is equal to the covariance between \( z \) and \( p/k^* \) divided by the standard deviation of \( p/k^* \). A few steps of algebra give the stated formula. The numerators of the limits are \( \lim_{h^2_s \to \infty, h^2_{q} \to 0} Var (E[z|p/k^*]) = \lim_{h^2_s \to 0, h^2_{q} \to \infty} Var (E[z|p/k^*]) = \sigma^2_z \left(1 + \alpha^2 \frac{\sigma^2_z}{\sigma^2_u}\right) \). The denominators are obtained by substituting for \( \theta \) into the investment equation:

\[
k^* \propto \left( \frac{\frac{1}{h^2_s + h^2_{q}}}{1 + \frac{1}{h^2_s + h^2_{q}}} \right) \left( h^2_s \theta + h^2_q \eta \right) \tag{19}
\]

\[
k^* \propto \left( \frac{\frac{1}{h^2_s + h^2_{q}}}{1 + \frac{1}{h^2_s + h^2_{q}}} \right) \left[ h^2_s s + h^2_q \eta + \frac{h^2_q}{h^2_s} \left( \frac{1 + \frac{1}{h^2_s + h^2_{q}}}{1 + \frac{1}{h^2_s + h^2_{q}}} \right) \alpha u \right]. \tag{20}
\]

We have \( \lim_{h^2_s \to \infty, h^2_{q} \to 0} Var (E[z|k^*]) = \sigma^2_z \left(1 + \alpha^2 \frac{\sigma^2_z}{\sigma^2_u}\right) \) and \( \lim_{h^2_s \to 0, h^2_{q} \to \infty} Var (E[z|k^*]) = \sigma^2_z \). Taking ratios gives the stated expressions. \( \square \)

Price informativeness (15) is increasing in the precision of both the market and internal signals, so it both reveals and reflects information (RPE and FPE). Prices also have a noise component. Investment, which is driven by the same set of signals, inherits the noise in prices only if prices reveal a lot of new information (RPE is high). In other words, the manager’s optimal learning rule provides a way to separate RPE from FPE. Specifically, when most information is produced outside the firm, investment inherits the noise component of prices and the two become equally informative, as seen in (16). By contrast, when most information is internal, prices remain noisy whereas investment informativeness does not, as seen in (17). Therefore, we can

Our technique for separating RPE and FPE depends crucially on the existence of noise.
or discount rate shocks in prices. In fact, noise is necessary for informed trading in the first
place (Milgrom and Stokey 1982). It also drives a wedge between price informativeness and
investment informativeness. The manager optimally varies the size of this wedge according
to the relative precision of internal and market signals. However, any variation in the noise
component itself presents a confounding effect. Fortunately, we can measure the amount of
noise, or discount rate variation, in prices from a regression of ex-post returns on price-to-
assets:

$$E[z - p/k^* | p/k^*] = \left( \frac{\alpha^2 \sigma_u^2}{\sigma_z^2} + \frac{\alpha^2 \sigma_u^2}{\sigma_y^2} \right) (p/k^*)$$.

(21)

The predicted variable $z - p/k^*$ is the firm’s dollar return per dollar of assets, though we use
percentage returns in our tests. The predicted variation of prices for returns is

$$\sqrt{\text{Var}(E[z - p/k^* | p/k^*])} = \frac{\alpha^2 \sigma_u^2}{\sqrt{\frac{\sigma_z^2}{1 + h_s^2 + h_y^2} + \alpha^2 \sigma_u^2}}$$.

(22)

This forecasting regression therefore allows us to detect a rise in discount rate variation that
could otherwise confound our results on informativeness.

So far, we have derived welfare-based measures of informativeness and developed tech-
niques for separating the revelatory from the forecasting component of prices. Our final task
is to link informativeness and financial development.

C. Information acquisition

On date 0, traders purchase information. To find an equilibrium, we consider the incentives
of individual traders to deviate by purchasing incremental signals. Suppose in equilibrium
traders purchase signals with precision $h_s/\sigma_z$. Together with the internal signal $\eta$ that is
transmitted via investment, traders form conditional estimates

\[ E [z \mid s, \eta] = \left( \frac{h_s^2 + h_\eta^2}{1 + \frac{1}{h_s^2 + h_\eta^2}} \right) (h_s^2 s + h_\eta^2 \eta). \] (23)

Let the remaining component of productivity be

\[ \epsilon = z - E [z \mid s, \eta] \] (24)

and suppose that trader \( i \) has the opportunity to purchase a fraction \( \delta < 1 \) of \( \epsilon \) in the form of an incremental signal:

\[ s^\delta = \sqrt{\delta \epsilon} + \sqrt{1 - \delta \epsilon}. \] (25)

with \( \epsilon^\delta \sim N(0, \text{Var}(\epsilon)) \) orthogonal to all other shocks.\(^8\) Intuitively, trader \( i \) deviates by obtaining additional information not available to other traders or the manager. For example, a trader might construct a more sophisticated valuation model. Trader \( i \) has total information

\[ \sigma_i^2 \equiv \text{Var} \left( E [z \mid s^\delta, s, \eta] \right) = \sigma_z^2 \left( \frac{1 + \frac{\delta}{h_s^2 + h_\eta^2}}{1 + \frac{1}{h_s^2 + h_\eta^2}} \right). \] (26)

To keep the analysis simple, we parameterize the total cost of information as

\[ c (\sigma_i^2) = \psi \left( \frac{\sigma_i^2}{\sigma_z^2 - \sigma_i^2} \right). \] (27)

Infinite precision \( \sigma_z^2 = \sigma_i^2 \) is prohibitively costly. The parameter \( \psi \) is related to the marginal cost of information:

\[ \frac{\partial c}{\partial \delta} (\sigma_i^2) = \psi \left[ \frac{1 + h_s^2 + h_\eta^2}{(1 - \delta)^2} \right]. \] (28)

\(^8\)Calculate \( \text{Var}(\epsilon) = \sigma_z^2 \left( \frac{1 + \frac{1}{h_s^2 + h_\eta^2}}{1 + \frac{1}{h_s^2 + h_\eta^2}} \right). \)
Traders face an increasing marginal cost curve and $\psi$ controls its steepness. We interpret $\psi$ as a measure of financial development in the production of information.

To find the optimal increment $\delta$, trader $i$ solves the date-0 problem

$$\max_{\delta} \mathbb{E} \left[ \max_{x} \mathbb{E} \left[ x (v (k^*) - p) | s^\delta, s, \eta \right] - \frac{\alpha}{2} x^2 \right] - c \left( \sigma_i^2 \right).$$

(29)

Portfolio demand is given by

$$x^* = 1 + \frac{1}{\alpha} \left( \sqrt{\delta s^\delta} - \alpha u \right) k^*.$$

(30)

Equipped with a superior forecast due to the incremental signal $s^\delta$, trader $i$ can achieve higher profits than her peers. The maximized inner objective gives

$$\max_{\delta} \mathbb{E} \left[ \frac{1}{2 \alpha} \left( \alpha + \left( \sqrt{\delta s^\delta} - \alpha u \right) k^* \right)^2 \right] - c \left( \sigma_i^2 \right).$$

(31)

We can characterize the information equilibrium with the following result.

**Proposition 3.** The equilibrium precision $h_s^2$ of the traders’ signal satisfies

$$\frac{1}{\alpha} \text{Var} \left( z - \mathbb{E} [z | s, \eta] \right) \text{Var} (k^*) = \left. \frac{\partial c}{\partial \delta} \left( \sigma_i^2 \right) \right|_{\delta=0}.$$  

(32)

This condition can also be expressed as

$$\alpha \psi \sigma_z^{-2} \left( 1 + h_s^2 + h_\eta^2 \right)^2 = \frac{1}{\gamma^2} \left( \frac{\sigma_z^2}{1 + h_s^2 + h_\eta^2} \right).$$  

(33)

**Proof.** Equilibrium is attained when $h_s^2$ is such that $\delta = 0$ is optimal. The incremental signal $s^\delta$ is orthogonal to both $k^*$ and $u$ since it is only available to trader $i$. Evaluating the first-order condition for (31) at $\delta = 0$ and using $\text{Var} (s^\delta) = \text{Var} \left( z - \mathbb{E} [z | s, \eta] \right)$ gives (32). The second formulation (33) obtains by substituting for the variance of $k^*$, $s^\delta$ and the marginal cost $\partial c/\partial \delta$.  

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We see the possibility of multiple equilibria as in Dow and Gorton (1997). If managers have little internal information, there is an equilibrium in which no information is produced, there is no investment, and hence no incentive to produce information. This corner equilibrium is marked by FPE but not RPE. It disappears if the internal signal is sufficiently useful. Nevertheless, we see a feedback loop between prices and investment: if traders acquire more information, prices become more informative, and so does investment. Stronger investment increases the scope for trading and further raises the incentive to acquire information.

Price informativeness is decreasing in the investment cost $\gamma$ and the trading cost $\alpha$. If $\gamma$ rises, we expect to see a tighter cross-sectional distribution of investment in the data. The internal precision $h_\eta$ has a subtle impact: on one hand it raises incentives to trade by increasing the scope of investment; on the other, it crowds out trading opportunities. Rising uncertainty $\sigma_z^2$ leads to an increase in price informativeness by raising the supply of information.

The remaining variation in price informativeness can be attributed to the cost of information $\psi$. More efficient information production unambiguously raises price informativeness. The effect on total spending, however, is ambiguous:

$$c(\sigma_i^2)|_{\delta=0} = \psi (h_s^2 + h_\eta^2). \tag{34}$$

Investors respond to lower information costs $\psi$ by increasing information purchases $h_s^2$. The net effect on spending can be positive or negative. By itself, rising information spending does not imply higher (or lower) price informativeness.

We summarize the model’s predictions in Table I. Our model shows that welfare is higher when investment is more efficient; that investment is more efficient when prices are more informative; that prices are more informative when investors acquire more information; and that investors acquire more information when information costs fall. In the next section, we document the evolution of informativeness empirically by calculating predicted variations.
Table I. Model predictions
This table shows the comparative statics of the model based on the informative equilibrium. “Price dispersion” is the cross-sectional standard deviation of the price-to-assets ratio \( p/k^* \). “Predicted variation” is the product of the regression coefficient and the standard deviation of the regressor in a forecasting regression. “Prices” refers to the price-to-assets ratio \( p/k^* \); “earnings” is earnings-over-assets \( z \); investment is \( k \); and returns are \( (v - p)/k^* \).

<table>
<thead>
<tr>
<th></th>
<th>Price dispersion</th>
<th>Earnings on prices</th>
<th>Earnings on investment</th>
<th>Returns on prices</th>
<th>Information spending</th>
</tr>
</thead>
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<tr>
<td>Uncertainty</td>
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<tr>
<td>Internal precision</td>
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<td>−</td>
<td>+/−</td>
</tr>
<tr>
<td>Position cost</td>
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<td>( \gamma )</td>
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<tr>
<td>Noise</td>
<td>( \sigma_u )</td>
<td>+/−</td>
<td>−</td>
<td>−</td>
<td>+</td>
</tr>
</tbody>
</table>

4 Data

We obtain stock prices from CRSP, and bond prices from the Lehman/Warga database and Mergent Fixed Income Datascope. The test on option listings use listing dates from the CBOE. All accounting measures are from COMPUSTAT. Our main sample period is from 1960 to 2011 at an annual frequency. Bond data is available since 1973. We also use daily stock price data in our announcement-day volatility tests, which starts in 1970.

Our key equity valuation measure is the log-ratio of market capitalization to total assets and our key bond valuation measure is a firm’s credit spread. We use equity and bond prices from the end of March and accounting variables from the end of the previous fiscal year, typically December. This ensures that market participants have access to our conditioning variables.

We measure future profitability as future EBIT over today’s assets. This allows firms to increase their profits by growing, as they do in our model. We measure current investment alternatively as the log-ratio of R&D or CAPX to assets, and future investment as the log-
ratio of future R&D or CAPX to today’s assets. We consider horizons of between one and three years.

We also measure the volatility of returns around earnings announcements as an indicator of price informativeness. Specifically, we calculate the three-day cumulative abnormal return (CAR) around each earnings announcement and take its absolute value. For comparison, we calculate the same measure on days with no earnings announcement. We calculate three-day turnover similarly.

In most tests, we limit attention to S&P 500 non-financial companies, which represent the bulk of the U.S. nonfinancial corporate sector. The set of firms in this sample has remained relatively stable over time, allowing us to compare the informativeness of their market prices over several decades. For comparison, we also report results for the full set of non-financial firms, whose composition has seen substantial change.

Table II about here.

The Data Appendix at the end of the paper explains our measures in greater detail. Table II presents summary statistics. S&P 500 stocks are typically more profitable than the universe of stocks. They invest more in absolute terms, but not relative to assets. Their credit spreads are only a bit lower. S&P 500 stocks are also less volatile unconditionally. Finally, they have relatively smaller announcement-day returns than all firms. Both groups see the magnitude of their returns as well as their turnover increase by more than 50% around earnings announcements.

Our model suggests that the dispersion in prices is a partial indicator of price informativeness (it also depends on noise). Figure 1 shows the distribution of the ratio of market capitalization to total assets \((M/A)\) over time for the non-financial firms in the S&P 500. For the bulk of the distribution, cross-sectional dispersion has remained stable, falling from 1960 to 1980 and then recovering. More prominently, in the second half of the 1990s valuations become dramatically more right-skewed. Skewness peaks in 2000 before subsiding.
The dot-com boom aside, price differentiation has grown modestly, though a few firms with very high valuations stand out. In the results section, we check whether these changes are associated with a better forecast of future profitability.

Figure 1 about here.

Figure 1 also shows that the cross-sectional distribution of profitability has remained stable and symmetric for firms in the S&P 500. By contrast, investment, specifically R&D expenditure, has both grown and become more skewed. We show that investment and valuation are related in the empirical section.

5 Empirical results

For our main results, we construct time series of predicted variations of prices for earnings, investment, and returns, and of investment for earnings. Guided by our model, we look for trends in these series as evidence of changing informativeness. We also conduct a cross-sectional test by comparing the price informativeness of stocks with and without listed options. As our final test, we look at the magnitudes of earnings surprises over time.

A. Market prices and earnings

We begin by measuring price informativeness, the predicted variation (the forecasting coefficient times the standard deviation of the regressor) of prices for future earnings. Our model shows that price informativeness is a key indicator of welfare. It also shows that prices both reveal new information (RPE) and reflect existing information (FPE). Although we are particularly interested in RPE since it represents the added value of the financial sector, it is also useful to see if overall price informativeness has changed over time since all information, regardless of its source, contributes to welfare. Later, we will separate RPE from FPE by also looking at investment.
We always control for current earnings and investment to avoid attributing obvious public information to prices. This raises the bar slightly, but by omitting many other readily available signals, we are giving prices a better shot at forecasting, which turns out to be a conservative stance given our results.

To ensure that our controls are available to investors at the time of forecasting, we always match accounting data for a given year with market prices from March of the following year. As most companies end their fiscal years in December, this means that our market prices are typically recorded three months after our accounting variables. This approach also errs on the side of giving market prices a better shot at forecasting. To control for discount rate effects, we include year-industry dummies (we also look at returns directly later in the paper).

In sum, we exploit within-industry cross-sectional differences in valuations to forecast earnings and investment. Our focus here is on S&P 500 firms. Later, we show results for the full set of stocks.

**Equity prices and earnings**

Our first regression forecasts future earnings with equity prices. We run

\[
\frac{E_{i,t+k}}{A_{i,t}} = a_t \log \left( \frac{M_{i,t}}{A_{i,t}} \right) \times \mathbf{1}_t + b_t \left( \frac{E_{i,t}}{A_{i,t}} \right) \times \mathbf{1}_t + c_{s(i,t),t} (\mathbf{1}_{SIC1}) \times (\mathbf{1}_t) + \epsilon_{i,t},
\]

where \( \mathbf{1}_t \) is an indicator variable for year \( t \) and \( \mathbf{1}_{SIC1} \) is an indicator variable at the one-digit SIC industry level. We take logs of the market-to-assets ratio to mitigate its skewness. By interacting all our predictors with year fixed effects, we avoid making a strong functional form assumption. We forecast at the one-, two-, and three-year horizons \((k = 1, 2, 3)\). We always scale by current assets as companies can legitimately boost profits by growing.

Figure 2 about here.
Figure 2 depicts the results of regression (35). The two plots on the left show the evolution of the coefficients $a_t$ at the one- and three-year horizons. The middle plots display the equity market-predicted variation, given by the product of the forecasting variable coefficient $a_t$ and its cross-sectional dispersion $\sigma_t (\log M/A)$. The predicted variation measures the size of the predictable component of earnings that is due to prices. The two right-most plots show the contribution to the regression $R^2$ from including market prices. Specifically, the marginal $R^2$ is defined as the difference between the $R^2$ from the full forecasting regression and the $R^2$ from a regression that omits $\log M/A$ as a predictor.

Figure 2 shows that market prices are positive predictors of future earnings at both the short and long horizons. The forecasting coefficient and marginal $R^2$ are a bit higher and the predicted variation is a bit larger at the 3-year horizon. The 3-year estimates are also somewhat noisier, but comfortably above zero. We note a drop in the predictive power of prices at the end of the NASDAQ boom in 2000, but this drop is short-lived. Overall, the coefficients $a_t$ remain flat throughout our sample.

We find no evidence of an increasing trend in equity price informativeness. The predicted variation of prices has remained remarkably stable over the past fifty years, the sharp drop around 2000 notwithstanding. Although prices do help separate firms that will be more profitable from those that will be less profitable, the extent to which they do so now is about the same as in the past.

**Bond prices and earnings**

Turning to the bond market, we check how credit spreads predict earnings. Analogously to our equity regression, we run

$$\frac{E_{i,t+k}}{A_{i,t}} = a_t (y_{i,t} - y_{0,t}) \times 1_t + b_t \left( \frac{E_{i,t}}{A_{i,t}} \right) \times 1_t + c_{n(i,t),t} (1_{\text{SIC1}}) \times (1_t) + \epsilon_{i,t}, \quad (36)$$

where $y_t - y_0$ is the yield of firm $i$’s bonds in excess of the duration-matched Treasury yield.
Figure 3 shows that the predictive power of yield spreads is modest, perhaps because most S&P 500 firms have sterling credit. The forecasting coefficients are rarely two standard errors from zero. Nevertheless, on average higher spreads are associated with slightly lower future earnings, as expected. Predictability is strongest in the late 1970s when credit risk was of particularly high concern. The marginal $R^2$ is reliably low and noisy.

Our next task is to check whether the stability of price informativeness reflects (i) unchanged information production on the part of investors (RPE), (ii) a substitution from internal to market-based information, or (iii) a rise in discount rate variation accompanied by higher information production. We examine (ii) by looking at investment and (iii) by looking at returns.

B. Investment and earnings

Our model shows that overall price informativeness could remain constant even if market-based information production (RPE) is rising as long as internal information production (FPE) is falling. In other words, firms could be substituting from internal to market-based sources of information in a way that leaves price informativeness constant. We also showed, however, that this substitution should make the predicted variations of prices and investment for earnings more similar. Since we found that price informativeness is constant, under this mechanism investment informativeness should come down. This happens because in order to keep price informativeness constant, internal and market-based information must be substituted one-for-one. But in that case investment informativeness has to fall since the presence of noise makes it difficult to extract information from prices.

We regress future earnings on current investment-over-assets. We present results for both R&D investment and CAPX. We include current earnings as a control together with our usual industry-times-year fixed effects. Specifically, the R&D regression has the following
form:

\[
\frac{E_{i,t+k}}{A_{i,t}} = a_t \left( \frac{R&D_{i,t}}{A_{i,t}} \right) \times 1_t + b_t \left( \frac{E_{i,t}}{A_{i,t}} \right) \times 1_t + c_{s(i,t),t} (1_{SIC1} \times (1_t) + \epsilon_{i,t}.
\]

The CAPX regression is analogous. We focus on the predicted variation \( a_t \times \sigma_t (R&D/A) \) (or \( a_t \times \sigma_t (CAPX/A) \) for CAPX) and we report the coefficients \( a_t \) and the contribution of the \( R&D \) variable to investment for completeness.

Figures 4 and 5 about here.

Figure 4 documents a generally positive relationship between R&D investment and future earnings, at least at the three-year horizon. Firms that undertake more R&D tend to be more profitable in the future, even after controlling for current profitability. By contrast, Figure 5 shows no evidence of a correlation between capital expenditure and future investment.

There is no apparent trend in investment informativeness that could unmask a trend in the RPE component of price informativeness. Our results so far are consistent with a stable amount of overall information, as well as a stable breakdown between market-based and internal information.

Overall, investment appears to be a fairly weak predictor of future earnings. Under our model, this leads to low overall wealth and welfare. However, it is plausible that investment, more so than prices, is measured with error. In fact, our price informativeness measures are generally higher than investment informativeness. Unlike the level, the lack of a time trend in investment informativeness is robust to measurement error, at least as long as it is constant.

C. Market prices and investment

To further explore the relationship between prices and investment, we leave out earnings and run forecasting regressions of future investment on prices. We call the resulting predicted
variation price informativeness for investment. In our model, it is equal to the price informativeness for earnings scaled by the adjustment cost. Intuitively, investment is proportional to expected earnings and prices are proportional to expected earnings plus noise. Thus, price informativeness for investment is driven by the size of the noise component and the adjustment cost.

**Equity prices and R&D expenditure**

We begin with R&D expenditure, which may be of particular interest as its funding requires well-developed equity markets due to low asset pledgeability. During our sample, the importance of R&D has increased, as has its dispersion across firms (see Figure 1).

We add current R&D as an additional control since R&D spending tends to persist. We run the regression

\[
\frac{R&D_{i,t+k}}{A_{i,t}} = a_t \log \left( \frac{M_{i,t}}{A_{i,t}} \right) \times 1_t + b_t \left( \frac{R&D_{i,t}}{A_{i,t}} \right) \times 1_t + c_t \left( \frac{E_{i,t}}{A_{i,t}} \right) \times 1_t + d_{s(i,t),t} (1SIC1) \times (1_t) + \epsilon_{i,t}.
\]

The results in Figure 6 show that higher market valuations are associated with more R&D spending: firms with high valuations invest more, as expected. This result holds even after controlling for current R&D (removing this control makes the effect larger).

The predicted variation shows a clear upward trend; prices have become stronger predictors of R&D. The effect is stronger at the three-year horizon, suggesting a substantially forward-looking relationship. Although it is tempting to interpret this result as increased information production, our results on earnings predictability are not consistent with this view. Within the context of our model, rising price informativeness for investment can be attributed to less noise in prices or lower adjustment costs. The evidence on noise later in the paper suggests it has not changed much. Outside our model, structural factors like the increased importance of technology may play a role, a possibility in line with our contrasting
Bond spreads and R&D expenditure

Turning to bond markets, Figure 7 shows no evidence that corporate bond spreads forecast R&D. The forecasting coefficients are close to zero and exhibit no trends. These results are not surprising as R&D is by nature not well-suited to bond financing. R&D-intensive technology firms tend to issue few bonds if any.

Equity prices and capital expenditure

Turning to tangible investment, we check whether market valuations are associated with higher CAPX. Analogously to the R&D regression, we run

$$\frac{CAPX_{i,t+k}}{A_{i,t}} = a_t \log \left( \frac{M_{i,t}}{A_{i,t}} \right) \times 1_t + b_t \left( \frac{CAPX_{i,t}}{A_{i,t}} \right) \times 1_t + c_t \left( \frac{E_{i,t}}{A_{i,t}} \right) \times 1_t$$

$$+ d_{s(i,t),t} (1_{SIC1}) \times (1_t) + \epsilon_{i,t}.$$

Figure 8 shows that a higher equity valuation is associated with more capital expenditure, particularly at the longer horizons. However, we find no evidence of a trend in the forecasting coefficient, the predicted variation, or the marginal $R^2$. This result contrasts with our findings for R&D and supports the interpretation that the nature of investment has changed in a way not captured by our model.

Bond spreads and capital expenditure

As with R&D expenditure (Figure 7), Figure 9 shows that lower bond spreads are not associated with higher capital expenditure. The forecasting coefficients are small and noisy,
and there is no evidence of a trend in the bond market-predicted variation or the marginal $R^2$.

D. Market prices and returns

Our model shows that price informativeness is affected by the level of noise, or discount rate variation, in prices. It is possible that an increase in noise could mask an increase in information production, leaving measured informativeness constant. To check this possibility, we run regressions of ex post returns on prices. In our model, prices orthogonalize returns and fundamentals, so expected returns depend solely on the noise term.

To implement this idea, we run our standard predictability regression with returns on the left, focusing on the three-year horizon (results are the same at shorter horizons):

$$\log R_{i,t+3} = a_t \log \left( \frac{M_{i,t}}{A_{i,t}} \right) \times 1_t + b_t \left( \frac{E_{i,t}}{A_{i,t}} \right) \times 1_t + c_{s(i,t),t} \left( 1_{SIC1} \right) \times (1_t) + \epsilon_{i,t}. \quad (37)$$

The results are presented in Figure 10. Overall, due to the high volatility of returns, the discount rate component of prices is less precisely measured than the earnings component. Although bumpy, the series is flat. A sharp drop in 2000 coincides with the end of the NASDAQ boom, but return predictability quickly recovers to its usual levels.

We conclude that there is no evidence of an increase in the discount rate component of price variation that could account for the result that price informativeness remains unchanged.

E. Comparison between S&P 500 firms and all firms

In this section, we compare the predictability results for S&P 500 firms to those of the universe of stocks. The results are presented in Figure 11. The top left panel shows a dramatic difference in fundamental uncertainty between the two groups. Starting in the 1970s, the dispersion in earnings across all firms increases dramatically until it levels off in
the mid 1980s at about three times the level observed among S&P 500 firms. This period coincides with the rise of NASDAQ. The tech boom of the late 1990s is associated with a second but smaller increase in earnings dispersion. In our model, higher earnings dispersion increases equilibrium level of informativeness because greater uncertainty provides a stronger incentive to acquire information.

Figure 11 about here.

The top right panel of Figure 11 shows that as the earnings dispersion of all firms has increased, so has their price dispersion. In contrast, S&P 500 firms show little evidence of increased price dispersion, except around 2000. In the context of our model, holding discount rate variation constant, increased price dispersion is associated with more informative prices and higher welfare. However, we see from the bottom two panels of Figure 11 that for all firms, the forecasting coefficient and its associated predicted variation drop precipitously around the same time as the dispersion across firms increases. Overall, the increased price dispersion does not appear to be related to earnings even at a three-year horizon.

If anything, price informativeness appears to be decreasing for all firms, but this is likely due to changing firm characteristics. Note that based on our model, higher uncertainty deepens the puzzle rather than resolving it. Instead, it must be the case that the average non-S&P 500 firm is more costly to value, not simply riskier. We view these results as motivating our focus on S&P 500 firms, whose observable characteristics have remained relatively stable. In the next section, we use a cross-sectional test to further control the composition of firms in our sample.

F. Option listing and informativeness

Our results show that price informativeness among S&P 500 firms is unchanged, whereas it has decreased among all firms, perhaps due to changing firm characteristics. This leaves the possibility that S&P 500 firms have also changed somehow even though their ex-post
earnings distribution has remained stable.

To check this possibility, we use cross-sectional variation in exposure to trading that is plausibly orthogonal to the unobserved factors that affect informativeness. Specifically, we compare firms that have options listed on the CBOE to those that do not. Option markets contribute to price discovery by increasing liquidity, providing embedded leverage, and offering a cheap way to take a short position. Mayhew and Mihov (2004) show that exchanges are more likely to list stocks with higher equity turnover, creating a potential bias towards finding higher informativeness among listed stocks.

Figure 12 about here.

To run the comparison, we calculate the predicted variation of prices for earnings based on regression (35) separately for listed and unlisted stocks. The results are in Figure 12. Price informativeness has remained flat for both groups, as it has for the overall market. There is no evidence that listed firms have higher price informativeness. This suggests that changing firm characteristics cannot account for the stability of price informativeness. The next section provides further support for this view with a test that includes firm fixed effects.

G. Volatility around earnings announcements

In this section, we look at volatility around earnings announcements as a model-free measure of informativeness. The idea is that better information should lead to smaller ex-post surprises. Here, we measure surprises with the magnitude of returns around earnings announcements. Specifically, for each firm in every year, we calculate three-day cumulative abnormal returns (CARs) around earnings announcements and take their absolute value. We also calculate share turnover during the same period. As a benchmark, we also report the same measures on non-announcement days. For a given level of overall volatility, the relative magnitude of announcement versus no-announcement returns reflects the ex-ante informativeness of market prices.
Figure 13 displays the results. Looking at S&P 500 firms, volatility on non-announcement days has remained flat, whereas announcement-day volatility has increased. At the start of the sample, volatility is similar across announcement and non-announcement days. By the end of the sample, volatility on announcement days is almost twice as high. In 2010, a typical three-day abnormal return is 5% on announcement days versus 2% on other days. This suggests that return surprises have grown rather than decreased over this period even as total volatility has remained stable.

For all firms, total volatility has increased somewhat as can be seen from the rising amount of volatility on non-announcement as well as announcement days. This observation further motivates our focus on S&P 500 firms. As with the S&P 500, the share of volatility on announcement days has risen dramatically so that in 2010 a typical three-day return is 8% around announcements versus 4% otherwise. Based on these results, we find no evidence of increased market price informativeness.

The bottom plots in Figure 13 give additional context. They show that as the relative magnitude of announcement-day returns has increased, so has the share of announcement-day turnover. Like returns, turnover is similar across different days at the beginning of the sample but twice as high on announcement days towards the end. In 2010, the typical stock experiences 5% turnover in the three days following an earnings announcement, versus 2.5% during other three-day periods. These findings suggest a link between increased trading and increased volatility around earnings announcements.

Changes in regulation are a plausible explanation for increasing return surprises. For example Reg FD in 2000 limited firms’ ability to disclose selective information. However, we see return surprises grow in the years prior to Reg FD. Nevertheless, it is still possible that tighter regulation has increased the cost of information production while other factors have increased it. Our framework does not allow us to decompose information costs further.

Table III about here.
Table III shows the results from a panel regression. We regress the difference in the magnitude of CARs between announcement and no-announcement days on five-year dummies, and in some cases turnover. Consistent with Figure 13, the relative magnitude of announcement-day abnormal returns starts off low and in fact drops a bit in the first five years, and then increases sharply around 1990. At the end of the sample, the difference in CARs is over 2% higher than at the beginning, and this number is highly statistically significant. The numbers are a bit bigger for all firms than for the S&P 500, but not by much.

The regression framework allows us to examine this trend within the firm, largely avoiding composition effects. We do this by including firm fixed effects in columns (2) and (4) of Table III. The results show that the relative increase in announcement surprises is almost as strong within firms as it is overall. For a given firm in the S&P 500, the relative magnitude of announcement-day returns is 1.5% bigger at the end of the sample than at the beginning. For all firms, the increase is over 2%.

As Figure 13 suggests, some of this increase is associated with an increase in relative turnover around announcement days. Columns (3) and (4) of Table III show that when we include the difference in turnover between announcement and no-announcement days, the magnitude of the trend in announcement-day returns is halved or nearly eliminated. For S&P 500 firms, the 2% increase drops to 0.1% and for all firms it drops from 2.8% to 1.3% when we include firm fixed effects.

These results suggest that markets today are just as surprised—if not more so—when firms release financial statements as in the past. These surprises are accompanied by a surge in trading activity. Based on this test, we find no evidence that financial markets have become more informative.
6 Conclusion

We examine the extent to which stock and bond prices predict future earnings. Our main finding is that financial market informativeness has not increased in the past fifty years. We decompose informativeness into a revelatory and a forecasting component by also looking at investment, and we find no evidence of increased information production in markets. We do find a stronger association between prices and R&D spending, but this does not translate into earnings predictability. We focus on S&P 500 firms, whose characteristics have remained stable. Among all firms, informativeness appears to decline, but this is likely due to changing firm characteristics. A cross-sectional test based on option listings supports our time series results. Finally, earnings surprises in returns have grown relative to total return volatility.

These results appear to contradict the view that improvements in information technology and liquidity have increased information production. A possible explanation is that the relevant constraint for investors lies in the ability to interpret information rather than the ability to record and transmit it. In the words of Herbert Simon (1996), “An information processing subsystem (a computer) will reduce the net demand on attention of the rest of the organization only if it absorbs more information, previously received by others, than it produces—if it listens and thinks more than it speaks.”
Data appendix

Equity market valuation

We use the ratio of market capitalization to total asset to capture the information contained in the equity market. The value of total asset is released in a firm’s 10-K form at the end of its fiscal year, usually in December. Market capitalization is based on the stock price at the end of March of the next year. In this way, the market price is guaranteed to capture public information on profitability and investment. Given our results, this approach is conservative in that it gives market participants a better shot at forecasting. Stock prices and volume are from the Center for Research in Security Prices (CRSP) during the period of 1960 to 2011.

Bond market valuation

We use the spread between corporate bond yields and Treasury yields to capture the information contained in bond prices. We collect month-end market prices of corporate bonds from the Lehman/Warga database and Mergent Fixed Income Datascope. These bonds are senior unsecured bonds with a fixed coupon schedule. The Lehman/Warga database covers the period from 1973 to 1997 (Warga (1991) has the details). Mergent Datascope provides daily bond yields from 1998 to 2010. To be consistent with the equity market valuation, we also use end-of-March yields.

To calculate the corporate credit spread, we match the yield on each individual bond to the yield on the Treasury with the closest maturity. The continuously-compounded zero-coupon Treasury yields are from the daily estimates of the U.S. Treasury yield curve reported in Gurkaynak, Sack, and Wright (2007). To mitigate the effect of outliers in our analysis, we follow Gilchrist and Zakrajsek (2007) and eliminate all observations with negative credit spreads and with spreads greater than 1,000 basis points. This selection criterion yields a sample of 4433 individual bonds issued by 615 firms during the period from 1973 to 2010. Our final sample contains about 18,000 firm-year observations with non-missing bond spreads.
Profitability and investment

Testing the predictions of our models requires empirical proxies for profitability and investment. A natural choice as the proxy for profitability is net income. This item represents the income of a company after all expenses such as income taxes and minority interest, but before provisions for common and/or preferred dividends. An alternative proxy is earnings before interest and taxes (EBIT), or equivalently operating income after depreciation (OIADP). These two items both represent the operating income (sales) of a company after deducting expenses for cost of goods sold, selling, general, and administrative expenses, and depreciation/amortization. In the empirical tests, we use EBIT (scaled by total asset). The results are similar using net income.

Investment by non-financial firms can be both tangible and intangible. For tangible investment, we use capital expenditures (‘CAPX’ in COMPUSTAT) as the proxy, which represents cash outflow used for a company’s property, plant and equipment, excluding amounts arising from acquisitions. For intangible investment, we use research and development (R&D) expense (denoted as ‘XRD’ in COMPUSTAT), which represents all costs incurred during the year that relate to the development of new products or services. Besides profitability and investment, we also collect other firm characteristics from COMPUSTAT such as total asset (‘AT’). We also obtain earnings announcement days from COMPUSTAT. This data starts in 1970 and refers to the first date on which earnings are published in the financial press and news wires.

Our measure of firm uncertainty uses data on analyst forecasts from I/B/E/S. We download the standard deviation of analyst forecasts for one-year-ahead earnings for each firm in every year. We take the average of this standard deviation within a year for each firm. To construct our uncertainty measure, we multiply by the number of shares, which converts the standard deviation into a total dollar amount, then divide by assets to get a measure of uncertainty as a percentage of firm assets.
References


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Rajan, Raghuram G., 2005, Has finance made the world riskier?, *Proceedings of the 2005 Jackson Hole Conference organized by the Kansas City Federal Reserve Bank*. 


Tobin, James, 1969, A general equilibrium approach to monetary theory, *Journal of Money, Credit and Banking* 1, 15–29.


### Table II. Summary statistics

Means and standard deviations of key variables for non-financial firms in S&P 500 index and in the universe. Market capitalization is from CRSP in millions of dollars. Total assets, EBIT, capital expenditure, and R&D are from COMPUSTAT in millions of dollars. Credit spreads are from the Lehman/Warga Database and Mergent Fixed Income Datascope, calculated in excess of the duration-matched Treasury bond, and reported in percent. Idiosyncratic volatility is the standard deviation of daily abnormal returns, in percent. Analyst dispersion over assets is the standard deviation in EPS forecasts from I/B/E/S, multiplied by the number of shares outstanding, and divided by total assets, reported in percent. Announcement |CAR| is the absolute value of a firm’s cumulative abnormal return over the three days following an earnings announcement, reported in percent. No-announcement |CAR| is for all other three-day periods. Announcement turnover and no-announcement turnover are calculated analogously. Next, log \((M/A)\) is the log-ratio of market cap to assets, \(E/A\) is EBIT over assets, log \((R&D/A)\) is the log-ratio of R&D over assets, and log \((CAPX/A)\) is the log-ratio of \(CAPX\) over assets. All ratios are winsorized at the 1% level. The main sample period is from 1960 to 2011. Bond data starts in 1973, analyst data in 1976, and earnings announcement data in 1970.

<table>
<thead>
<tr>
<th></th>
<th>S&amp;P 500</th>
<th></th>
<th>All Firms</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median St. Dev.</td>
<td>Mean</td>
</tr>
<tr>
<td>Market capitalization</td>
<td>6,942</td>
<td>1,283</td>
<td>1,067</td>
</tr>
<tr>
<td>Total assets</td>
<td>7,439</td>
<td>1,885</td>
<td>1,244</td>
</tr>
<tr>
<td>EBIT</td>
<td>715</td>
<td>180</td>
<td>108</td>
</tr>
<tr>
<td>R&amp;D</td>
<td>276</td>
<td>48</td>
<td>42</td>
</tr>
<tr>
<td>Capital expenditure</td>
<td>473</td>
<td>117</td>
<td>79</td>
</tr>
<tr>
<td>Credit spread</td>
<td>1.59</td>
<td>1.13</td>
<td>1.61</td>
</tr>
<tr>
<td>Idiosyncratic volatility</td>
<td>1.88</td>
<td>1.66</td>
<td>3.83</td>
</tr>
<tr>
<td>Analyst dispersion / Assets</td>
<td>0.07</td>
<td>0.00</td>
<td>0.54</td>
</tr>
<tr>
<td>Announcement</td>
<td>CAR</td>
<td></td>
<td>3.68</td>
</tr>
<tr>
<td>No-announcement</td>
<td>CAR</td>
<td></td>
<td>2.32</td>
</tr>
<tr>
<td>Announcement turnover</td>
<td>2.61</td>
<td>1.29</td>
<td>3.73</td>
</tr>
<tr>
<td>No-announcement turnover</td>
<td>1.61</td>
<td>0.96</td>
<td>2.02</td>
</tr>
<tr>
<td>log ((M/A))</td>
<td>-0.18</td>
<td>-0.22</td>
<td>-0.21</td>
</tr>
<tr>
<td>(E/A)</td>
<td>0.12</td>
<td>0.11</td>
<td>0.03</td>
</tr>
<tr>
<td>(R&amp;D/A)</td>
<td>0.04</td>
<td>0.02</td>
<td>0.07</td>
</tr>
<tr>
<td>(CAPX/A)</td>
<td>0.12</td>
<td>0.07</td>
<td>0.13</td>
</tr>
<tr>
<td>Firm-year observations</td>
<td>23,463</td>
<td></td>
<td>202,703</td>
</tr>
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</table>
The magnitude of earnings surprises

Results from the panel regression

\[ |CAR_{i,t}^{\text{Ann.}}| - |CAR_{i,t}^{\text{No ann.}}| = a + b_1 t + c (Turn_{\text{Ann.}} - Turn_{\text{No ann.}})_{i,t} + f_i + e_{i,t}. \]

The dependent variable is the difference in the magnitude of cumulative abnormal returns (CARs) on announcement and no-announcement days for a given firm in a given year. On the right side, we include dummies for successive five-year periods (the omitted category is 1970 to 1975). Both CARs and turnover are in percent. In columns (3) and (4), we include the difference in share turnover between announcement and no-announcement days, \( Turn_{\text{Ann.}} - Turn_{\text{No ann.}} \). Columns (2) and (4) include firm fixed effects. Standard errors are clustered by year. We report separate results for S&P 500 firms and for all firms.

<table>
<thead>
<tr>
<th></th>
<th>S&amp;P 500</th>
<th>All Firms</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.619***</td>
<td>0.833***</td>
</tr>
<tr>
<td></td>
<td>(0.080)</td>
<td>(0.079)</td>
</tr>
<tr>
<td>1976 to 1980</td>
<td>-0.340***</td>
<td>-0.314***</td>
</tr>
<tr>
<td></td>
<td>(0.094)</td>
<td>(0.093)</td>
</tr>
<tr>
<td>1981 to 1985</td>
<td>-0.205**</td>
<td>-0.250***</td>
</tr>
<tr>
<td></td>
<td>(0.089)</td>
<td>(0.089)</td>
</tr>
<tr>
<td>1986 to 1990</td>
<td>0.069</td>
<td>-0.009</td>
</tr>
<tr>
<td></td>
<td>(0.133)</td>
<td>(0.139)</td>
</tr>
<tr>
<td>1991 to 1995</td>
<td>0.478***</td>
<td>0.387***</td>
</tr>
<tr>
<td></td>
<td>(0.116)</td>
<td>(0.107)</td>
</tr>
<tr>
<td>1996 to 2000</td>
<td>0.906***</td>
<td>0.715***</td>
</tr>
<tr>
<td></td>
<td>(0.229)</td>
<td>(0.221)</td>
</tr>
<tr>
<td>2001 to 2005</td>
<td>1.694***</td>
<td>1.221***</td>
</tr>
<tr>
<td></td>
<td>(0.178)</td>
<td>(0.200)</td>
</tr>
<tr>
<td>2006 to 2011</td>
<td>2.081***</td>
<td>1.505***</td>
</tr>
<tr>
<td></td>
<td>(0.187)</td>
<td>(0.181)</td>
</tr>
<tr>
<td>Turn_{Ann.}</td>
<td>0.653***</td>
<td>0.779***</td>
</tr>
<tr>
<td>-Turn_{No ann.}</td>
<td>(0.042)</td>
<td>(0.053)</td>
</tr>
<tr>
<td>Firm F.E.</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>R²</td>
<td>0.128</td>
<td>0.298</td>
</tr>
</tbody>
</table>
Figure 1. The distribution of valuation, profitability, and investment

The sample consists of non-financial firms in the S&P 500 index. The four plots show medians (red line), 10th and 90th percentiles (shaded bands). $M/A$ is market capitalization over assets. $E/A$ is EBIT over assets. $R&D/A$ and $CAPX/A$ are analogous for research and development, and capital expenditure, respectively.
Figure 2. Forecasting earnings with equity prices

Results from the regression

$$\frac{E_{i,t+k}}{A_{i,t}} = a_t \log \left( \frac{M_{i,t}}{A_{i,t}} \right) \times 1_t + b_t \left( \frac{E_{i,t}}{A_{i,t}} \right) \times 1_t + c_{s(i,t),t} (1_{SIC1}) \times (1_t) + \epsilon_{i,t}. $$

Market cap $M$ is measured as of the end of March following the firm’s fiscal year end. Earnings $E$ are measured as EBIT. $SIC1$ is the one-digit SIC code. The values for $k$ are 1 and 3 years. The sample consists of all S&P 500 non-financial firms from 1960 to 2010. The coefficients $a_t$ are plotted inside a 95% confidence band. The equity market-predicted variation is $a_t \times \sigma_t (\log M/A)$. The marginal $R^2$ is the difference between the full-regression $R^2$ and the $R^2$ from a regression omitting $\log M/A$. 
Figure 3. Forecasting earnings with bond spreads

Results from the regression

$$\frac{E_{i,t+k}}{A_{i,t}} = a_t (y_{i,t} - y_{0,t}) \times 1_t + b_t \left( \frac{E_{i,t}}{A_{i,t}} \right) \times 1_t + c_{s(i,t),t} (1_{SIC1}) \times (1_t) + \epsilon_{i,t}. $$

Corporate bond spread $y_{i,t} - y_{0,t}$ is the difference between the average yield of corporate bonds issued by firm $i$ in year $t$ and the duration-matched Treasury yield in year $t$. Yields are measured at the end of March following the firm’s fiscal year end. Earnings $E$ are measured as EBIT. $SIC1$ is the one-digit SIC code. The values for $k$ are 1 and 3 years. The sample consists of all S&P 500 non-financial firms from 1972 to 2010, when bond data is available. The coefficients $a_t$ are plotted inside a 95% confidence band. The bond market-predicted variation is $a_t \times \sigma_t (y - y_0)$. The marginal $R^2$ is the difference between the full-regression $R^2$ and the $R^2$ from a regression omitting corporate bond spread $(y - y_0)$.
Figure 4. Forecasting earnings with R&D expenditure

Results from the regression

\[
E_{i,t+k} = a_t \left( \frac{R&D_{i,t}}{A_{i,t}} \right) \times 1_t + b_t \left( \frac{E_{i,t}}{A_{i,t}} \right) \times 1_t + c_t \left( \frac{1}{SIC_{i,t}} \right) \times 1_t + \epsilon_{i,t}
\]

Earnings \( E \) are measured as EBIT. \( SIC_1 \) is the one-digit SIC code. The values for \( k \) are 1 and 3 years. The sample consists of all S&P 500 non-financial firms from 1960 to 2010. The coefficients \( a_t \) are plotted inside a 95% confidence band. The R&D-predicted variation is \( a_t \times \sigma_t \left( \frac{R&D}{A} \right) \). The marginal \( R^2 \) is the difference between the full-regression \( R^2 \) and the \( R^2 \) from a regression omitting R&D/A.

Coefficients, \( a_t \)

Predicted variation, \( a_t \times \sigma_t \left( \frac{R&D}{A} \right) \)

Marginal \( R^2 \)
Results from the regression

\[
\frac{E_{i,t+k}}{A_{i,t}} = a_t \left( \frac{CAPX_{i,t}}{A_{i,t}} \right) \times 1_t + b_t \left( \frac{E_{i,t}}{A_{i,t}} \right) \times 1_t + c_{s,t} (1_{SIC1}) \times (1_t) + \epsilon_{i,t}.
\]

Earnings $E$ are measured as EBIT. $SIC1$ is the one-digit SIC code. The values for $k$ are 1 and 3 years. The sample consists of all S&P 500 non-financial firms from 1960 to 2010. The coefficients $a_t$ are plotted inside a 95% confidence band. The R&D-predicted variation is $a_t \times \sigma_t (CAPX/A)$. The marginal $R^2$ is the difference between the full-regression $R^2$ and the $R^2$ from a regression omitting $CAPX/A$. 

### Coefficients, $a_t$

- $k = 1$

### Predicted variation, $a_t \times \sigma_t (CAPX/A)$

- $k = 1$

### Marginal $R^2$

- $k = 1$
Figure 6. Forecasting R&D expenditure with equity prices

Results from the regression

\[
\frac{R&DD_{i,t+k}}{A_{i,t}} = a_t \log \left( \frac{M_{i,t}}{A_{i,t}} \right) \times 1_t + b_t \left( \frac{R&DD_{i,t}}{A_{i,t}} \right) \times 1_t + c_t \left( \frac{E_{i,t}}{A_{i,t}} \right) \times 1_t + d_{s(i,t),t} (1_{SIC1}) \times (1_t) + \epsilon_{i,t}.
\]

Market cap $M$ is measured as of the end of March following the firm’s fiscal year end. Earnings $E$ are measured as EBIT. $SIC1$ is the one-digit SIC code. The values for $k$ are 1 and 3 years. The sample consists of all S&P 500 non-financial firms from 1960 to 2010. The coefficients $a_t$ are plotted inside a 95% confidence band. The equity market-predicted variation is $a_t \times \sigma_t (\log M/A)$. The marginal $R^2$ is the difference between the full-regression $R^2$ and the $R^2$ from a regression omitting $\log M/A$.

Coefficients, $a_t$

Predicted variation, $a_t \times \sigma_t (\log M/A)$

Marginal $R^2$
Forecasting R&D expenditure with bond spreads

Results from the regression

$$\frac{R&D_{i,t+k}}{A_{i,t}} = a_t (y_{i,t} - y_{0,t}) \times 1_t + b_t (\bar{A}_{i,t}) \times 1_t + c_t (E_{i,t} A_{i,t}) \times 1_t + d_t (1_{SIC1}) \times 1_t + \epsilon_{i,t}.$$ 

The yield spread $y_{i,t} - y_{0,t}$ is the difference between the average yield of corporate bonds issued by firm $i$ in year $t$ and the duration-matched Treasury bond yield in year $t$. Yields are measured at the end of March following the firm's fiscal year end. Earnings $E_i$ are measured at EBIT. $SIC$ is the one-digit SIC code. The values for $k$ are 1 and 3 years. The sample consists of all S&P 500 non-financial firms from 1972 to 2010, when bond data is available. The coefficients $a_t$ are plotted inside a 95% confidence band. The bond market-predicted variation is $a_t \times \sigma_t (y - y_0)$. The marginal $R^2$ is the difference between the full-regression $R^2$ and the $R^2$ from a regression omitting $y - y_0$.
Figure 8. Forecasting capital expenditure with equity prices

Results from the regression

\[
\frac{CAPX_{i,t+k}}{A_{i,t}} = a_t \log \left( \frac{M_{i,t}}{A_{i,t}} \right) \times 1_t + b_t \left( \frac{CAPX_{i,t}}{A_{i,t}} \right) \times 1_t + c_t \left( \frac{E_{i,t}}{A_{i,t}} \right) \times 1_t + d_{s(i,t),t} \left( 1_{SIC1} \right) \times (1_t) + \epsilon_{i,t}.
\]

Market cap \( M \) is measured as of the end of March following the firm’s fiscal year end. Earnings \( E \) are measured as EBIT. \( SIC1 \) is the one-digit SIC code. The values for \( k \) are 1 and 3 years. The sample consists of all S&P 500 non-financial firms from 1960 to 2010. The coefficients \( a_t \) are plotted inside a 95% confidence band. The equity market-predicted variation is \( a_t \times \sigma_t (\log M/A) \). The marginal \( R^2 \) is the difference between the full-regression \( R^2 \) and the \( R^2 \) from a regression omitting \( \log M/A \).
Results from the regression

\[
\frac{\text{CAPX}_{i,t}}{A_{i,t}} = a_t (y_{i,t} - y_{0,t}) + b_t \left( \frac{E_{i,t}}{A_{i,t}} \right) + c_t (E_{i,t} A_{i,t}) + d_t \left( \frac{1}{SIC_1} \right) + \epsilon_{i,t}.
\]

Corporate bond spread \( y_{i,t} - y_{0,t} \) is the difference between the average yield of corporate bonds issued by firm \( i \) in year \( t \) and the duration-matched Treasury yield in year \( t \). Yields are measured at the end of March following the firm's fiscal year end. Earnings \( E \) are measured as EBIT. \( SIC_1 \) is the one-digit SIC code. The values for \( k \) are 1 and 3 years. The sample consists of all S&P 500 non-financial firms from 1972 to 2010, when bond data is available. The sample consists of all S&P 500 non-financial firms from 1972 to 2010, when bond data is available.

Coefficients, \( a_t \)

Predicted variation, \( a_t \times \sigma_t (y - y_0) \)

Marginal \( R^2 \)

The bond market-predicted variation is \( a_t \times \sigma_t (y - y_0) \). The marginal \( R^2 \) is the difference between the full-regression \( R^2 \) and the \( R^2 \) from a regression omitting \( y - y_0 \).
Figure 10. Forecasting returns with equity prices

This figure plots the predicted variation of prices for returns and earnings. The predicted variation is defined as $a_t \times \sigma_t (\log M/A)$ from the forecasting regression

$$\log R_{i,t \rightarrow t+3} / \frac{E_{i,t+3}}{A_{i,t}} = a_t \log \left( \frac{M_{i,t}}{A_{i,t}} \right) \times 1_t + b_t \left( \frac{E_{i,t}}{A_{i,t}} \right) \times 1_t + c_{s(i,t),t} (1_{SIC1}) \times (1_t) + \epsilon_{i,t}.$$  

Market cap $M$ is measured as of the end of March following the firm’s fiscal year end. Earnings $E$ are measured as EBIT. $SIC1$ is the one-digit SIC code. The sample consists of all S&P 500 non-financial firms from 1960 to 2010.
Figure 11. S&P 500 versus all firms

Earnings dispersion, market price dispersion, and results from the regression

\[
\frac{E_{i,t+3}}{A_{i,t}} = a_t \log \left( \frac{M_{i,t}}{A_{i,t}} \right) \times 1_t + b_t \left( \frac{E_{i,t}}{A_{i,t}} \right) \times 1_t + c_{s(i,t),t} \left( 1_{SIC1} \right) \times (1_t) + \epsilon_{i,t}.
\]

for the S&P 500 non-financial versus all non-financial firms. Dispersion is measured as the cross-sectional standard deviation in \( E/A \) and \( \log M/A \) for a given year. Market cap \( M \) is measured as of the end of March following the firm’s fiscal year end. Earnings \( E \) are measured as EBIT. \( SIC1 \) is the one-digit SIC code. The equity market-predicted variation is \( a_t \times \sigma_t (\log M/A) \).
Figure 12. Option listing and price informativeness
This figure plots the predicted variation of prices for earnings for stocks with and without listed options. The predicted variation is defined as $a_t \times \sigma_t \left( \log \frac{M}{A} \right)$ from the forecasting regression

$$\frac{E_{i,t+3}}{A_{i,t}} = a_t \log \left( \frac{M_{i,t}}{A_{i,t}} \right) \times 1_t + b_t \left( \frac{E_{i,t}}{A_{i,t}} \right) \times 1_t + c_{s(i,t),t} \left( 1_{SIC1} \right) \times (1_t) + \epsilon_{i,t}.$$  

The sample starts in 1973 when the first equity options were introduced by the CBOE.
Figure 13. Volatility and turnover around earnings announcements

For each firm in every year, we calculate the absolute value of three-day abnormal returns, $|CA_{R_{t\to t+2}}|$, around earnings announcements (“Announcement”) and on all other days (“No announcement”). We also calculate three-day turnover, $Turnover_{t\to t+2}$, (volume divided by shares outstanding) analogously. We plot averages across firms by year for the S&P 500 non-financial firms, and for all firms. Announcement dates are from COMPUSTAT and returns and volume are from CRSP. The sample period is from 1970 to 2011.